

# Brain-Computer Interface Controlled Robotic Gait Orthosis: A Case Report

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**Abstract—Background:** Excessive reliance on wheelchairs in individuals with tetraplegia or paraplegia due to spinal cord injury (SCI) leads to many medical co-morbidities, such as cardiovascular disease, metabolic derangements, osteoporosis, and pressure ulcers. Treatment of these conditions contributes to the majority of SCI health care costs. Restoring able-body-like ambulation in this patient population can potentially reduce the incidence of these medical co-morbidities, in addition to increasing independence and quality of life. However, no biomedical solution exists that can reverse this loss of neurological function, and hence novel methods are needed. Brain-computer interface (BCI) controlled lower extremity prosthesis may constitute one such novel approach.

**Methods:** An able-bodied subject underwent electroencephalogram (EEG) recording while engaged in alternating epochs of idling and walking kinesthetic motor imagery (KMI). These data were analyzed to generate an EEG prediction model for online BCI operation. A commercial robotic gait orthosis (RoGO) system (suspended over a treadmill), was interfaced with the BCI computer to allow for computerized control. In an online test, the subject was tasked to ambulate using the BCI-RoGO system when prompted by computerized cues. The performance of this system was assessed with cross-correlation analysis, and omission and false alarm rates.

**Results:** The offline accuracy of the EEG prediction model was  $94.8 \pm 0.8\%$  (chance: 50%). The cross-correlation between instructional cues and the subject's BCI-RoGO walking epochs averaged over 5 online sessions was  $0.809 \pm 0.056$  ( $p\text{-value} < 10^{-5}$ ). Also, there were on average 0.8 false alarms per session and no omissions.

**Conclusion:** These results provide preliminary evidence that restoring brain-controlled ambulation is feasible. Future work will test the function of this system in individuals with SCI. If successful, this may justify future development of BCI-controlled lower extremity prostheses for free overground walking for those with complete motor SCI. Finally, this system can also be applied to incomplete motor SCI, where it could lead to improved neurological outcomes beyond those of standard physiotherapy.

**Index Terms—**Brain computer interface, gait, walking, robotic gait orthosis, Lokomat.

## I. INTRODUCTION

INDIVIDUALS with tetraplegia or paraplegia due to spinal cord injury (SCI) are unable to walk and most are wheelchair bound. Decreased physical activity associated with

prolonged wheelchair use leads to a wide range of comorbidities such as metabolic derangements, heart disease, osteoporosis, and pressure ulcers [1]. Unfortunately, no biomedical solutions can reverse this loss of neurological function, and treatment of these comorbidities contributes to the bulk of medical care costs for this patient population [1]. While commercially available lower extremity prostheses can help restore basic ambulation via robust manual control, their adoption amongst the SCI community remains low, likely due to cost, bulkiness, energy expenditure inefficiencies, and the need to frequently don and doff the device. Hence, novel approaches are needed to restore able-bodied-like ambulation in patients with SCI. If successful, these will improve the quality of life in this population, and reduce the incidence and cost of medical comorbidities and care-giver burden.

A brain-computer interface (BCI) controlled lower extremity prosthesis may be one such novel approach. It can be envisioned that a combination of invasive brain signal acquisition system as well as implantable functional electrical stimulation (FES) electrodes can potentially act as a permanent BCI prosthesis. However, for safety reasons, the feasibility of brain controlled ambulation must first be established with noninvasive systems.

This concept was explored in the authors' prior work [2]–[4], in which subjects (both able-bodied and SCI) used an electroencephalogram (EEG) based BCI to control the ambulation of an avatar within a virtual reality environment. In these studies, subjects utilized idling and walking kinesthetic motor imagery (KMI) to complete a goal-oriented task of walking the avatar along a linear path and making stops at 10 designated points. In addition, two out of five SCI subjects achieved BCI control that approached that of a manually controlled joystick. While these results suggest that accurate BCI control of ambulation is possible after SCI, the translation of this technology from virtual reality to a physical prosthesis has not been achieved.

In this study, the authors report on the first case of integration of an EEG-based BCI system with a robotic gait orthosis (RoGO), and its successful operation by a single able-bodied subject. This approach was taken in order to ascertain the feasibility of such a system and justify the risks associated with its testing (e.g. falls, lower extremity fractures, syncope from orthostatic hypotension) in SCI subjects. The success reported here warrants further investigation of the system's function in subjects with SCI.

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## II. METHODS

To facilitate the development of a BCI-controlled RoGO, EEG data were recorded from an able-bodied subject engaged in alternating epochs of idling and walking KMI. These data were then analyzed offline to generate an EEG prediction model for online BCI operation. A commercial RoGO system (suspended over a treadmill), was interfaced with the BCI computer to allow for computerized control. In an online test, the subject was tasked to ambulate using the BCI-RoGO system when prompted by computerized cues. The performance of this system was assessed by calculating the cross-correlation and latency between the computerized cues and BCI-RoGO response, as well as omission and false alarm rates.

### A. Training Data Acquisition

Ethical approval was obtained from the Institutional Review Board at the Long Beach Veterans Affairs Medical Center (LBVA) and the University of California, Irvine (UCI). An able-bodied male subject (age 42) gave informed consent to participate in the study. The subject had ~5 hr of related BCI experience operating a BCI-controlled ambulation of an avatar in a virtual reality environment [3]. First, an actively shielded 64-channel EEG cap was mounted on the subject's head with impedances reduced to <10 K $\Omega$ . EEG signals were acquired using 2 linked NeXus-32 bioamplifiers (Mind Media, Roermond-Herten, The Netherlands) at a sampling rate of 256 Hz. The subject was suspended into a treadmill-equipped RoGO (Lokomat, Hocoma, Volketswil, Switzerland) using partial weight unloading (see Fig. 1). Note that unlike overground orthoses, this system facilitates safe and easy testing suitable for early development of BCI-prostheses for ambulation. Finally, EEG data were collected as the subject alternated between 30-sec epochs of idling and walking KMI for a total of 10 min, as directed by the computer cues. Note that KMI entails vivid imagination of walking during walking KMI cues, and relaxation during idling cues. During this procedure, the subject stood still with arms at the sides.

### B. Electromyogram and Leg Movement Measurement

Electromyogram (EMG) was measured to rule out BCI control by voluntary leg movements. To this end, baseline lower extremity EMG were measured under 3 conditions: *active walking* (subject voluntarily walks while the RoGO servos are turned off); *cooperative walking* (subject walks synergistically with the RoGO); and *passive walking* (the subject is fully relaxed while the RoGO makes walking movements). Three pairs of surface EMG electrodes were placed over the left quadriceps, tibialis anterior, and gastrocnemius (Fig. 1), and signals were acquired with a bioamplifier (MP150, Biopac, Goleta, CA), bandpass filtered (0.1-1000 Hz), and sampled at 4 KHz. In addition, a gyroscope (Wii Motion Plus, Nintendo, Kyoto, Japan) with a custom wristwatch-like enclosure was strapped to the distal left lower leg (proximal to the ankle), and was used to measure leg movements (Fig. 1) [5]. Approximately 85% body-weight unloading was necessary for proper RoGO operation, and the walking velocity was set at 2 km/hr.

### C. Offline Analysis

An EEG prediction model was generated using the methods described in [3], which are briefly summarized here. First, the training EEG data were subjected to an automated algorithm to exclude EEG channels with excessive artifacts. The EEG epochs corresponding to “idling” and “walking” states were then transformed into the frequency domain, and their power spectral densities (PSD) were integrated over 2-Hz bins. The data then underwent dimensionality reduction using a combination of classwise principal component analysis (CPCA) [6], [7] and approximate information discriminant analysis (AIDA) [8]. The resulting 1-D spatio-spectral features were extracted by:

$$f = T_A \Phi_C(d) \quad (1)$$

where  $f \in \mathbb{R}$  is the feature,  $d \in \mathbb{R}^{B \times C}$  are single-trial spatio-spectral EEG data ( $B$ -the number of frequency bins,  $C$ -the number of retained EEG channels),  $\Phi_C : \mathbb{R}^{B \times C} \rightarrow \mathbb{R}^m$  is a piecewise linear mapping from the data space to the  $m$ -dimensional CPCA-subspace, and  $T_A : \mathbb{R}^m \rightarrow \mathbb{R}$  is an AIDA transformation matrix. Detailed descriptions of these techniques are found in [7], [8]. A linear Bayesian classifier:

$$f^* \in \begin{cases} \mathcal{I}, & \text{if } P(\mathcal{I}|f^*) > P(\mathcal{W}|f^*) \\ \mathcal{W}, & \text{otherwise} \end{cases} \quad (2)$$

was then designed in the feature domain, where  $P(\mathcal{I}|f^*)$  and  $P(\mathcal{W}|f^*)$  are the posterior probabilities of “idling” and “walking” classes, respectively. The performance of the Bayesian classifier (2), expressed as a classification accuracy, was then assessed by performing stratified 10-fold cross-validation [9]. This was achieved by using 90% of the EEG data to train the parameters of the CPCA-AIDA transformation and the classifier. The remaining 10% of data then underwent the above transformation and classification. This process was repeated 10 times, each time using a different set of 9 folds for training and the remaining 1 fold for testing. Finally, the optimal frequency range  $[F_L, F_H]$  was found by increasing the lower and upper frequency bounds and repeating the above procedure until the classifier performance stopped improving [10]. The parameters of the prediction model, including  $[F_L, F_H]$ , the CPCA-AIDA transformation, and the classifier parameters, were then saved for future real-time EEG analysis during online BCI-RoGO operation. The above signal processing and pattern recognition algorithms were implemented into the BCI software and optimized for real-time operation [10].

### D. BCI-RoGO Integration

To comply with the institutional restrictions that prohibit software installation, the RoGO computer was interfaced with the BCI using a pair of microcontrollers (Arduino, Smart-Projects, Turin, Italy) in order to perform mouse hardware emulation. Microcontroller #1 relayed commands from the BCI computer to microcontroller #2 via an Inter-Integrated Circuit (I<sup>2</sup>C) connection. Microcontroller #2 then acted as a slave device programmed with a mouse emulation firmware [11] to automatically manipulate the RoGO's user interface.

This setup enabled the BCI computer to directly control the RoGO idling and walking functions.

### E. Online Signal Analysis

During online BCI-RoGO operation, 0.75-sec segments of EEG data were acquired every 0.25 sec in a sliding overlapping window manner. The PSD of the retained EEG channels were calculated for each of these segments and used as the input for the signal processing algorithms (Section II-C). The posterior probabilities of idling and walking classes were calculated using the Bayes rule [similar to Eq. (2)].

### F. Calibration

Similar to the authors' prior work [2], [3], [10], [12], [13], the BCI-RoGO system is modeled as a binary state machine with "idling" and "walking" states. This step is necessary to reduce noise in the online BCI operation and minimize the mental workload of the subject. To this end, the posterior probability was averaged over 2 sec of EEG data,  $\bar{P}(W|f^*)$ , and compared to two thresholds,  $T_I$  and  $T_W$ , to initiate state transitions. Specifically, the system transitioned from "idling" to "walking" state (and vice versa) when  $\bar{P} > T_W$  ( $\bar{P} < T_I$ ), respectively. Otherwise, the system remained in the current state.

The values of  $T_I$  and  $T_W$  were determined after a short calibration procedure as follows. The system was set to run in the online mode (with RoGO walking disabled) as the subject alternated between idling or walking KMI for  $\sim 5$  min. The values of  $\bar{P}$  were plotted in a histogram to help empirically determine the values of  $T_I$  and  $T_W$ . A brief familiarization online session with feedback was used to further fine tune these threshold values.

### G. Online Evaluation

In an online evaluation, the subject, while mounted in the RoGO, used idling/walking KMI to elicit 5 alternating 1-min epochs of BCI-RoGO idling/walking, as directed by the computer cues. Ideally, during walking KMI, the underlying EEG changes should initiate and maintain BCI-RoGO walking until walking KMI stops. The subject was instructed to make no voluntary movements and to keep arms still at the side. Left leg EMG and movements were measured as described in Section II-B. This evaluation task was performed 5 times in a single experimental day.

Online performance was assessed with the following metrics [10], [12], [13]:

- 1) Cross-correlation between the cues and BCI-RoGO walking
- 2) Omissions (OM)—failure to activate BCI-RoGO walking during "Walk" cues
- 3) False Alarms (FA)—initiation of BCI-RoGO walking during "Idle" cues

Analysis of EMG and leg movement data was performed to ascertain that RoGO walking was entirely BCI controlled. First, to demonstrate that covert movements were not used to initiate BCI-RoGO walking, gyroscope and rectified EMG data

(in the 40-400 Hz band) were compared to the BCI decoded "walking" states in each session. Ideally, the initiation of these states should precede EMG activity and leg movements. Then, to establish that voluntary movements were not used to maintain BCI-RoGO walking, EMG during these epochs were compared to the baselines (see Section II-B). To this end, EMG data were segmented by individual steps based on the leg movement pattern [5], as measured by the gyroscope. The PSD of these EMG segments were then averaged and compared to those of the baseline walking conditions. Ideally, the EMG power during BCI-RoGO walking should be similar to that of *passive walking* and different from those of *active* and *cooperative walking*.

## III. RESULTS

The subject successfully underwent the training EEG procedure, and subjectively stated that he imagined himself walking and standing during the "Walk" and "Idle" cues respectively. An EEG prediction model was generated as described in Section II-C based on training EEG data (Section II-A). This offline analysis resulted in a model classification accuracy of  $94.8 \pm 0.8\%$  (chance: 50%). A representative EEG feature extraction map is shown in Fig. 1. After the calibration procedure (Section II-F), a histogram of posterior probabilities was plotted (Fig. 1). Based on this and a familiarization trial, the values  $T_I = 0.04$  and  $T_W = 0.65$  were ultimately chosen.

The performances from the 5 online sessions are summarized in Table I. The average cross-correlation between instructional cues and the subject's BCI-RoGO walking epochs was  $0.809 \pm 0.056$ . For control, the maximum cross-correlation between instructional cues and simulated BCI operation using 100,000 Monte Carlo random walk runs was 0.408, indicating that the cross-correlations in Table I were significant with an empirical p-value  $< 10^{-5}$ . Also, there were no omissions. However, in the first 3 sessions, one to two brief false alarms occurred, and there were none during the final 2 sessions. False alarm epochs averaged 7.08 sec, but much of this time can be attributed to the RoGO's locked-in startup sequence ( $\sim 5$  sec). A video of a representative online session is provided as downloadable supplemental media. Alternatively, an online version can be found at: <http://www.youtube.com/watch?v=W97Z8fEAQ7g>.

TABLE I  
ONLINE PERFORMANCES: CROSS-CORRELATION BETWEEN BCI-RoGO WALKING AND CUES AT SPECIFIC LAGS, NUMBER OF OMISSIONS AND FALSE ALARMS, AND AVERAGE DURATION OF FALSE ALARM EPOCHS.

Sess.	Xcorr. (lag in sec)	OM	FA (avg. duration in sec)
1	0.771 (10.25)	0	1 (12.0)
2	0.741 (4.50)	0	2 (5.5 $\pm$ 0.0)
3	0.804 (3.50)	0	1 (5.3)
4	0.861 (4.50)	0	0
5	0.870 (12.00)	0	0
Avg.	$0.809 \pm 0.056$ (6.95 $\pm$ 3.89)	0	0.8 (7.08 $\pm$ 3.28)

The EMG and leg movement data from online sessions were analyzed as described in Section II-G. EMG and gyroscope measurements indicated that no movement occurred prior to the initiation of BCI decoded "walking" states (see Fig. 2).

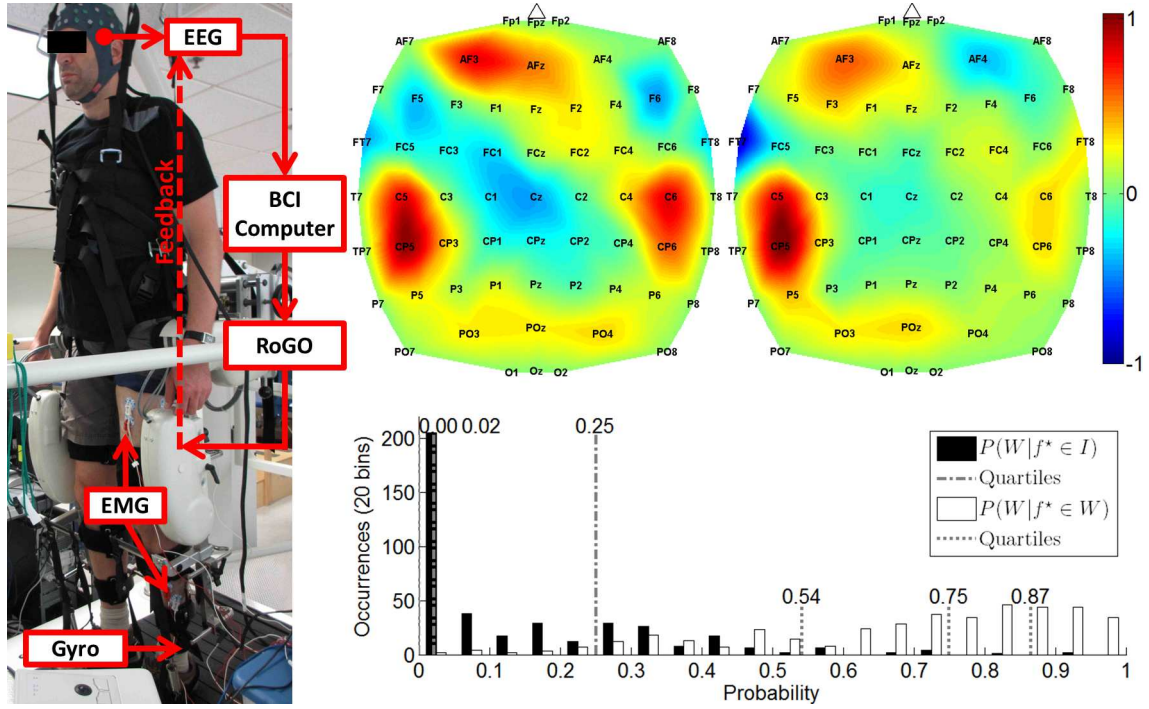


Fig. 1. *Left*: The experimental setup showing the subject suspended in the RoGO, while donning an EEG cap, surface EMG electrodes, and a gyroscope on the left leg. A monitor (not shown), placed in front of the subject at eye-level, presented instructional cues. *Top Right*: The CPCA-AIDA feature extraction maps at the 8-10 Hz bin. Since feature extraction is piecewise linear, there is one map for each of the 2 classes. Brain areas with values close to +1 or -1 are most salient for distinguishing between idling and walking classes at this frequency. *Bottom Right*: Histogram of averaged posterior probabilities,  $\bar{P}(W|f^*)$ .

When compared to the baselines, the EMG during online BCI-RoGO walking in all 3 muscle groups were statistically different from those of *active* or *cooperative walking* conditions ( $p < 10^{-13}$ ), and were not different from those of passive walking ( $p = 0.37$ ). These results confirm that the BCI-RoGO system was wholly BCI controlled. Note that *passive walking* is known to generate EMG activity [14], hence a similar level of activity during BCI-RoGO walking (Fig. 3) is expected.

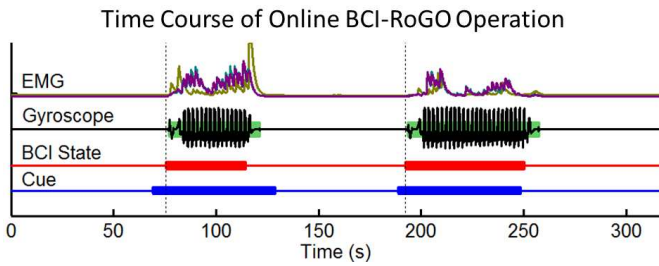


Fig. 2. Results from a representative online session, showing epochs of idling and BCI-RoGO walking (red trace: decoded BCI states; blue trace: instructional cues). The thick/thin blocks indicate walking/idling. Corresponding EMG (gold: quadriceps; teal: tibialis anterior; purple: gastrocnemius) and BCI-RoGO walking as detected by the gyroscope are also shown.

#### IV. DISCUSSION AND CONCLUSION

The EEG prediction model in this study had higher offline classification accuracy than those in related BCI walking avatar studies [2], [3]. Note that this was achieved despite the subject being suspended in the RoGO (as opposed to

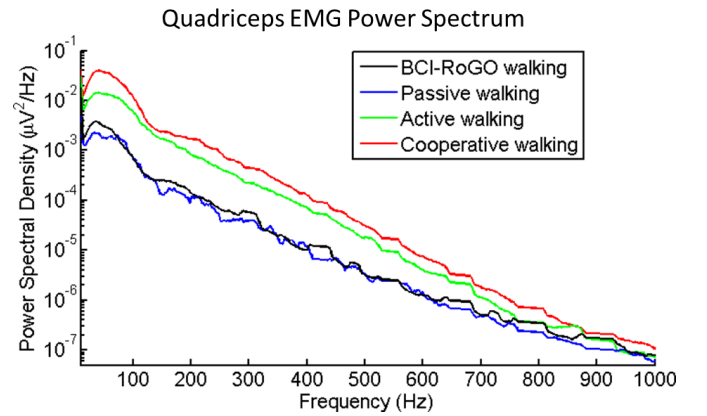


Fig. 3. Representative EMG PSD of the quadriceps, demonstrating that EMG during BCI-RoGO walking are different from baseline active or cooperative walking conditions, and are similar to passive walking.

being seated as in [2], [3]). The salient brain areas underlying walking KMI (Fig. 1) likely overlie the pre-frontal cortex, supplementary motor (SMA), and arm sensorimotor representation areas, and are consistent with those previously reported. For example, activation of the pre-frontal cortex and SMA during walking motor imagery has been described in functional imaging studies (e.g. [15]). Similarly, involvement of bilateral arm areas during walking KMI has been reported in [3] and may be associated with arm swing imagery. This EEG prediction model was further validated by generating separable posterior probability distributions (Fig. 1) and facilitating highly accurate online BCI-RoGO control. Finally, since

it was generated through a data-driven procedure, the model is subject specific and may accommodate neurophysiological variability across subjects [2], [3].

The average online cross-correlation (Table I) was higher than those achieved with lower (0.67) and upper (0.78) extremity BCI-prostheses [10], [12], despite EEG being acquired under more hostile (ambulatory) conditions. This implies that future BCI-prostheses for overground walking may be feasible. Additionally, the subject's online BCI-RoGO operation was purposeful with a 100% response rate (no omissions), and by the end of the experiment, the subject had no false alarms. Although brief in duration, false alarms carry the risk of bodily harm, and this problem must be addressed in the development of future BCI-prostheses for overground walking. Table I also shows that the maximum correlation is attained at an average lag of 6.95 sec. Most of this lag can be attributed to the RoGO's locked-in power-down sequence ( $\sim 5$  sec). Minor sources of delay include a combination of user response time and the 2-sec long posterior probability averaging window (see Section II-F). This delay can potentially be minimized with additional user training in a controlled environment. Also, reducing the averaging window may eliminate some of the delay at the expense of increasing the false alarm and omission rates, and this trade-off will be examined in future studies.

With only  $\sim 5$  hr of BCI experience (operating the BCI walking avatar in [2], [3]), the subject attained a high-level of control of the BCI-RoGO system after undergoing a series of short procedures (10 min training data acquisition, 5 min calibration, 5 min familiarization). This indicates that a data-driven EEG prediction model as well as prior virtual reality training may have facilitated this rapid acquisition of BCI control. In addition, this model enables BCI operation by an intuitive control strategy, i.e. walking KMI to induce walking and idling KMI to stop. This is in contrast to requiring subjects to undergo months of training in order to acquire a completely new skill of modulating pre-selected EEG signal features as frequently done in operant conditioning BCI studies.

Based on the above observations, this data-driven BCI approach may be necessitated for future intuitive control and practical application of BCI-controlled lower extremity prostheses for SCI users. This approach would enable SCI subjects to use intuitive BCI control strategies such as attempted (albeit ineffective) walking or walking KMI. Similar to the able-bodied subject here, this can potentially be accomplished with minimal user training and supervision from the experiment operator. This will enhance the appeal and practicality of future BCI-controlled lower extremity prostheses for ambulation by reducing the time burden and the associated costs.

In conclusion, these results provide convincing evidence that BCI control of ambulation is possible, which warrants future studies to test the function of this system in SCI subjects. Since SCI users were able to operate the BCI-walking simulator [3], [4], it is expected that they can readily transfer their skills to the BCI-RoGO system like the able-bodied subject here. If successful, such a system may justify future development of BCI-controlled lower extremity prostheses for free overground walking for those with complete motor SCI. This includes addressing issues such as additional degrees of freedom (e.g.

turning, velocity, sitting, standing), as well as appropriate solutions for signal acquisition (e.g. invasive recordings). Finally, the current BCI-RoGO system can also be applied to gait rehabilitation in incomplete motor SCI, where the addition of a Hebbian learning mechanism could improve neurological outcomes beyond those of standard physiotherapy.

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